

TRAFFIC SIGN RECOGNITION AND DETECTION using CNN

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Abstract

Roadside traffic indicators including yield and speed restriction signs are automatically detected using traffic sign classification. The evolution of traffic sign recognition systems that operate automatically regarding "smarter automobiles." For self-driving cars to effectively understand and comprehend the road, the need for recognizing traffic signs. Similar to this, for the purpose of support and safeguard drivers, "driver alert" systems in automobiles need to comprehend the surrounding road. With our technology, drivers wouldn't have to take their eyes off the road to see and understand traffic signs. Convolution neural networks allow for accurate classification of the signboards. More layers can be added to increase the precision. Here, training and testing are done using the GTSRB dataset; by optimizing the settings, traffic signs are reliably classified into 43 types, and detection speed also rises.

Keywords

Convolutional Neural Network, Smarter Cars

1 Introduction

Road safety depends on the recognition and detection of traffic signs, which might be difficult to do. A traffic sign is a signpost on a road that forbids certain behaviors and the significant of taking some sort of action. Road users are directed or controlled by traffic signs to abide by traffic laws. Traffic signs are erected at junctions and other places where a lot of cars pass by on a daily basis in many different nations.

According to estimates from the World Health Organization (WHO), 1.3 million people perish in auto accidents each year. The greater part of traffic fatalities worldwide (93%) take place in poor and middle-income nations. People in these nations frequently cause accidents by not understanding or following traffic laws.

Governments have the authority to post traffic signs, and private groups or people can assist motorists in need of guidance on appropriate driving practices highways. It involves recognizing road markers, also known as traffic signals, and traffic signs in a video sequence that is displayed in Figure 1. It is capable of detecting pedestrian crossings, speed restrictions, traffic lights, and more. Other uses for traffic sign detection include following individuals or objects in films. This technique consists of two main parts: the first is identifying the existence of traffic signs and road markings (traffic signals); the second uses computer vision techniques to extract information from these identified traffic signs and road markings.

To some extent, identifying and displaying the indicators will aid in accident prevention. Most of the time, traffic signs are not visible or are not positioned well. It's been difficult to input a fuzzy picture. Nevertheless, the convolution neural network simplifies the process because its several layers aid in processing the image by flattening it and generating the clearest output possible for processing further. Additionally, it upgraded the model with a sound module, making the traffic sign visible to the driver. Therefore, it can be helpful to have a speaker to announce the traffic sign. These recognition algorithms work well in automated vehicles. When

read aloud, the signs are a useful tool, and drivers should not miss out.

Traffic signs were previously recognized and classified using traditional computer vision algorithms, which required laborious human labor to construct necessary attributes in images. Deep learning was used to solve this issue, and the outcome was the evolution of a convolution neural network (CNN) model with several layers: Pooling, Convolution, and Completely linked. These layers will carry out the detection procedure that classifies traffic signs accurately and determines the characteristics that are most effective for the task at hand. It will first gather the data and forward it to the convolution layer, which is responsible for extracting the features from the supplied input images. The picture



Figure 1. Traffic Signs

is then transferred to the pooling layer, which reduces the convolved feature map's size. The weights between two are then covered by the fully connected layer neurons. It also includes the prejudices, which are the mistakes. It serves as a link between two strata. In order to acquire the final output, the image is ultimately transferred to the output layer.

2 Related Work

Intelligent and self-driving cars have already been developed using convolution network-trained models with several proposed detection and recognition techniques. A traffic sign identification and recognition system that can identify the sign in an image taken by the car's camera is described in this paper [14]. The thrice sequential procedure are usually involved in image analysis: detection, segmentation, and classification. The sign is subjected to edge detection and then segmentation in order to separate it from the background. Using the GTSRB and GTSDDB datasets, a simple feature selection and extraction method has been proposed. These datasets include real scene maps with a range of intricate and challenging-to-distinguish traffic signs employed and well sophisticated traffic signs with features including sign tilt, uneven lighting, occlusion, and similar background colors.

The authors proposed a method that uses straightforward feature extraction from pictures to identify and detect traffic signs. The road sign is taken out of the utilizing edge detection and filtering methods to create a background image. A CNN is used to create a traffic sign categorization system that can identify and categorize different types of signs. This algorithm alerts and warns drivers to avoid breaking the law. An end-to-end system for real-time traffic sign detection and recognition using image pre-processing, localization, and classification was presented by the authors of [13]. The sixteen most popular categories of traffic signs can be categorized using the proposed method.

In [12], the authors developed a data-driven, efficient system for identifying and detecting traffic signs by using a convolutional neural network (CNN) with high detection accuracy and excellent results in the training and awarding processes. A CNN built using the transfer learning approach is shown in [11]. A small number of traditional traffic training samples are used to achieve efficient regional convolutional neural network (RCNN) recognition, whereas a large data set is used to train Deep CNN. Using Li-Fi (Light Fidelity) technology, [21] presents

an intelligent vehicle-to-vehicle and vehicle-to-traffic signal communication system that gives the neighbouring automobile the necessary information. The study also covers the challenges and limitations of technology in order to further improve communication.

3 Methodology

3.1 Data Set:

Making use of the widely used German Traffic Sign Recognition Benchmark (GTSRB) data collection. A large dataset is needed prior to trying detection or classification. It is necessary to train a model on a high-quality, diverse dataset. The database includes a train folder with pictures of traffic signs in 43 different classes and a test folder with over 12,000 images for testing, as shown in Figure 2. Three pieces comprise the dataset: training, testing, and validation. The training dataset is the volume of data that was used to build the model. A trained prediction model is used to make predictions for the test dataset.

Hyperparameters that control the learning process and improve accuracy include the number of epochs and the choice of activation functions. Most of the time, the model is evaluated, and the validation dataset is used to update the hyperparameters. The test dataset is used only after the model has been trained. It is employed to assess how well the model can forecast the future. Figure 3 displays sample images of traffic signs.



Figure 3 Sample traffic sign images

3.2 Constructing the CNN Architecture:

A CNN-based model [7] for image-based traffic sign identification and recognition is put on in this work. A CNN prototype was created with both the ResNet and AlexNet topologies. AlexNet [20] employs the Relu activation function depicted in Figure 4 and has eight layers in total: three fully linked layers, a Max pooling layer, five convolution layers, and three other levels.

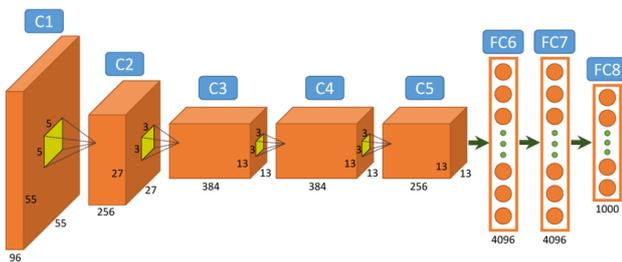


Figure 4 AlexNet Architecture

The ResNet [22] network is depicted in Figure 5 with a 34-layer network design that is inspired by VGG19 and to which the shortcut there is now a connection. These shortcut linkages then cause the architecture to change into a residual network.

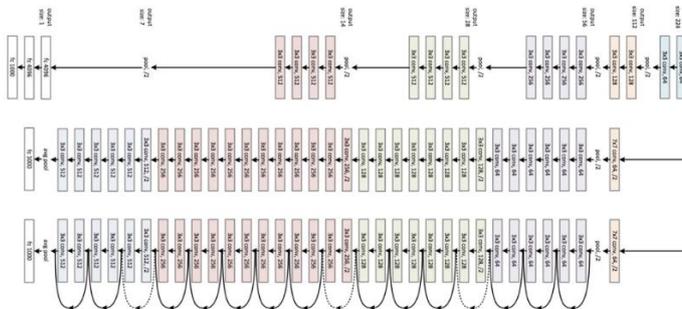


Figure 5 ResNet Architecture

3.3 Proposed Method:

The suggested system broadcasts the name of the sign along with its classification, which is its main focus after taking a picture. The suggested model's workflow involves feeding an input image into the AlexNet convolution layer and then using ResNet CNN to train it using the provided dataset. As seen in Figure 6, the outcomes of the AlexNet and ResNet are then categorized and split into classes.

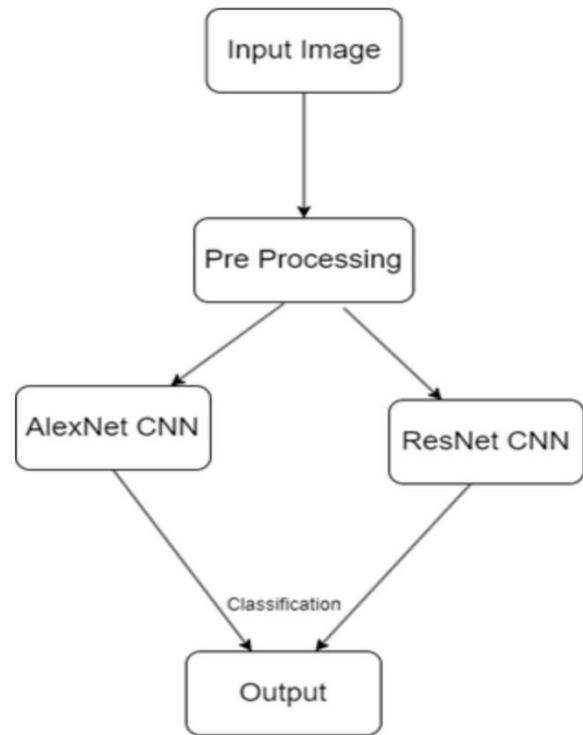


Figure 6. Proposed model flow process

4 Experimentation

In this study, the GTSRB dataset was used to test the ability of the pre-trained models AlexNet and ResNet to recognize traffic signs.

4.1 Processing:

Preprocessing is the process of transforming the data into an analysis-ready format. The training and testing datasets are divided into smaller ones, and the photos are used to repeatedly apply the pre-processing procedures to each dataset. First, the image is converted into a pixel grid. The gray-scale function receives the array of pixels as input. As seen in Figure 7, the gray-scale process turns colorful images into colorless gray-scale ones.

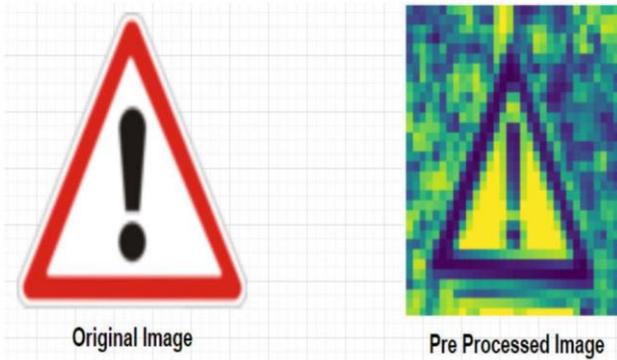


Figure 7. Sample Pre-processed Image

4.2 Implementation

With regard to accuracy, this model outperformed the others. A CNN model is employed in the first segment utilizing an picture as the input. After processing, one of the 43 classes is produced as the output, as seen in Figure 8. If there's no traffic sign in a certain image, the user gets a "No Sign Detected" prompt.

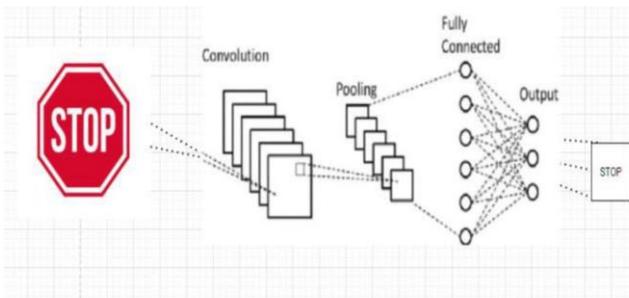


Figure 8. Output Class "Stop"

5 Results and Discussion

Traffic sign classification automatically recognizes and groups traffic signs according to their class, including stop, speed restriction, caution, and other signs. The training set has a roughly 95% accuracy for correctly detecting and classifying the images of traffic signs; the testing set also shows a 95% accuracy, and the validation set offers a 95% accuracy. The validation set yields results with an accuracy percentage of 92.4%. As per the confusion matrix, 90.3% of the testing set's findings were accurate. The results showed that recall was 98.06% and precision was 97.8%. The traffic sign detected,

accuracy, class number, and time spent are displayed in Table 1.

Table 1: Time taken, class number, accuracy, and detected traffic sign.

Detected Traffic Sign	Accuracy	Class Number	Time Taken(ms)
Stop	98.36%	14	20-40
Yield	97.8%	26	20-40
Speed Limit 30	97.67%	2	20-40

Accuracy was the selected performance indicator for the model, and it makes sense for the traffic sign dataset. By employing hyperparameters more skillfully, such example by modifying the or either raising the learning rate or the number of epochs. During testing using validation data, a confusion matrix—often displayed in tabular form and valid for classification problems—is used to assess the model's performance and ascertain the number of properly and incorrectly selected class labels. Figures 9 and 10 display the plotted graphs for the accuracy and loss measures.

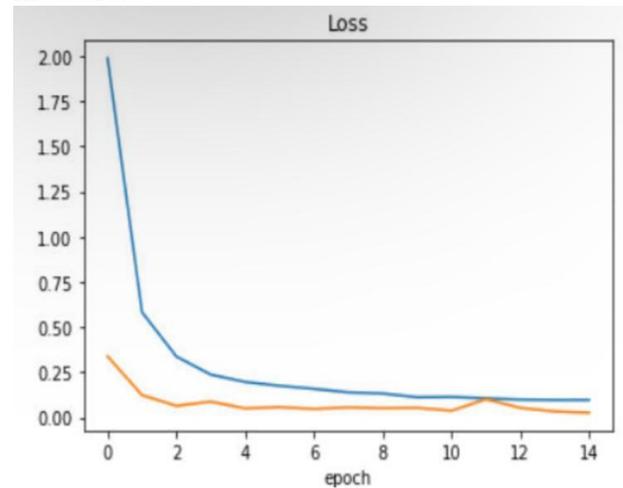


Figure 9. Loss Curve

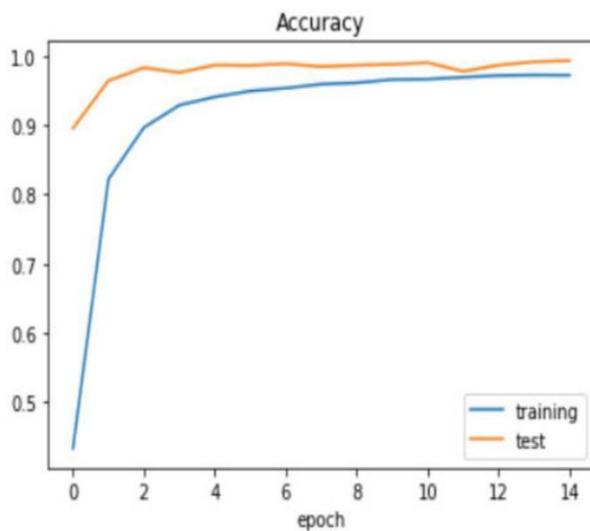


Figure 10. Accuracy Curve

Through an analysis of the model's accuracy and loss, we may determine that our model produces positive and encouraging outcomes. For photos that are hazy or imprecise, the accuracy rate is also around 98%.

6 Conclusion

This paper proposes a model of an efficient convolutional neural network-based traffic sign identification system. Cars must have this kind of system in order to guarantee the safety of the roads. We've talked about how deep learning, together with a variety of pre-processing and visualization techniques and model design experiments, can be used to reliably classify traffic signs. We created an easy-to-use CNN model that can recognise road traffic signs with accuracy. To obtain great accuracy, the parameters of the created neural network model are calibrated accurately. On training and testing sets, the average accuracy is more than 90%.

Reference

[1] "Traffic Sign Classification Using CNN," Preeti Bailke, Kunjal Agrawal, IJRASET 2022.
 [2] V. Viswanath Sheno, B. Venkateswarlu "CAViaR-WS- HAN: water sailfish-based hierarchical attention network with conditional autoregressive value at risk for emotion classification in COVID-19 text review data" Social Network

Analysis and Mining 2022.

[3] M. V. V., Sudarsa et al. "APMWMM: Method for Investigating Malware on Windows Machine through Machine Learning" (2022) International Conference on Applied Artificial Intelligence and Computing, ICAAIC 2022. Proceedings.

[4] "Automatic Recommendations Over the Places Using Built-In Service Google Maps" (2022) Lecture Notes in Electrical Engineering by Hrushikesava Raju et al.

[5] "DPMLT: Diabetes Prediction Using Machine Learning Techniques" Sushanth, K. K., et al. (2022) Proceedings of the International Conference on ICEARS 2022: Electronics and Renewable Systems.

[6] Loukya, M., et al. "Comparative Analysis of Machine Learning Algorithms for Customer Loan Approval Prediction." 2022: Proceedings of the 2nd International Conference on Smart Energy and Artificial Intelligence (ICAIS 2022).

[7] In the 2nd International Conference on Artificial Intelligence and Smart Energy, ICAIS 2022, proceedings, Srinivas, P., and Devabhaktuni, "Detection of COVID Disease from CT Scan Images using CNN Model" (2022).

[8] "A Novel Privacy Preserving Biometric Authentication Scheme Using Polynomial Time Key Algorithm in Cloud Computing," BhavaniDasari, D., et al. The 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS 2021) Proceedings.

[9] Hrushikesava Raju, et al. "YOLOv3-Based Smart Camera for Monkeys: A Novel IoT Approach for Monkey Detection and Control" (2021) Records of the Fifth International I-SMAC 2021 Conference

[10] "ERDNS: Ensemble of Random Forest, Decision Tree, and Naive Bayes Kernel Through Stacking for Efficient Cross Site Scripting Attack Classification," by A. Niranjan et al. (2021) Interactions in Computer and Data Science.

[11] Rosemol Xavier, Ashly Benny, Ivin Johnson K, and Arjun Dileep. "Traffic Sign Detection Based on Convolutional Neural Network." IJRASET 2021.

[12] Vandana Singh, Omkar Kadam, and Saurabh Dubey "Traffic Sign Detection and Recognition using Convolution Neural Network(CNN)" IRJET 2021.

[13] "TRAFFIC SIGN DETECTION USING CONVOLUTION NEURAL NETWORK," G. Bharath Kumar, N. Anupama Rani, IJCRT 2020.